# New Technologies Can Cost Effectively Reduce Oil and Gas Methane Emissions, but Policies Will Require Careful Design to Establish Mitigation Equivalence

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**ABSTRACT:** Reducing methane emissions from oil and gas systems is a central component of US and international climate policy. Leak detection and repair (LDAR) programs using optical gas imaging (OGI)-based surveys are routinely used to mitigate fugitive emissions or leaks. Recently, new technologies and platforms such as planes, drones, and satellites promise more cost-effective mitigation than existing approaches. To be approved for use in LDAR programs, new technologies must demonstrate emissions mitigation equivalent to existing approaches. In this work, we use the FEAST modeling tool to (a) identify cost vs mitigation trade-offs that arise from using new technologies and (b) provide a framework for effective design of alternative LDAR programs. We identify several critical insights. First, LDAR programs can trade sensitivity for speed without sacrificing mitigation outcomes. Second, low sensitivity or high detection threshold technologies have an effective upper bound on achievable mitigation that is independent of the survey frequency. Third, the cost effectiveness of tiered LDAR programs using site-level detection technologies depends on their ability to distinguish leaks from routine venting. Finally, "technology equivalence" based on mitigation outcomes differs across basins and should be evaluated independently. The FEAST model will enable operators and regulators to systematically evaluate new technologies in next-generation LDAR programs.

**KEYWORDS:** methane emissions, leak detection and repair, new technologies, FEAST, equivalence, methane policy
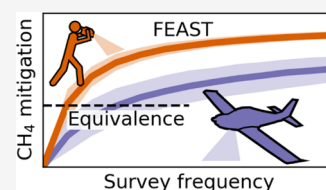
## 1. INTRODUCTION

Methane emissions from petroleum and natural gas systems accounted for 28% of US methane emissions in 2018, based on the Environmental Protection Agency's (EPA) greenhouse gas inventory (GHGI).[1] Furthermore, several recent studies have shown that official GHGI estimates likely underestimate methane emissions from natural gas systems.[2−6] Methane is the primary constituent of natural gas and has a global warming potential 34 times that of carbon dioxide over 100 years and 86 times over 20 years.[2] Therefore, reducing methane emissions from oil and gas operations is critical to realize GHG emissions benefits from recent coal-to-gas fuel switching in the power sector.[7−9] In addition, addressing methane emissions reduces volatile organic compounds coemitted from oil and gas operations, thereby improving local air quality.[10] Most importantly, minimizing methane leakage is a critical interim measure on the pathway to net-zero greenhouse gas emissions that will eventually require significant reductions in the combustion of all fossil fuels, including natural gas.[11,12]

State and federal governments throughout North America have enacted regulations in recent years to address methane emissions from oil and gas activity. California, Colorado, Pennsylvania, and several other states now require periodic leak detection and repair (LDAR) programs at upstream and midstream facilities to find and fix leaks.[13−16] Separately, some oil and gas companies have also implemented voluntary LDAR programs to reduce methane leakage from their operations.[17] The most common technologies approved by regulators and used in these LDAR programs include EPA's Method 21 and optical gas imaging (OGI)-based infrared cameras. Recent field work has shown that these OGI-based LDAR surveys have been effective in reducing emissions over several years.[17] Despite this success, there are challenges in scaling OGI-based LDAR to achieve rapid emission detection across vast geographic and temporal scales.

OGI surveys require an operator to manually inspect every potential leak source. Existing LDAR requirements typically specify one to four OGI surveys per year. The efficacy of these programs is limited by the probability that large unintended emissions (referred to as fugitive emissions or leaks) will persist for many months before detection. Ensuring that large emitters are quickly found and repaired therefore requires frequent LDAR surveys. However, frequent OGI-based LDAR surveys across thousands of sites quickly become logistically challenging and cost prohibitive.

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Recently, several companies have developed novel approaches to methane leak detection that address the survey frequency limitation of OGI surveys.[18−20] Based on publicly available information, we can define three broad classes of new detection methods:

(1) Novel component or equipment-level survey methods: OGI and EPA Method 21 surveys inspect every component and identify the source of emissions as part of the inspection. Drone- and some truck- and aerial platforms provide similar specificity at potentially higher survey speed and lower cost. Technologies in this class were tested during the Stanford/EDF mobile monitoring challenge and other studies.[18,20,21]

(2) Site- or equipment-level screening methods: Rapid site-level screening may be used to identify high-emitting sites that warrant component-level secondary follow-up surveys. Site-level screening techniques were also tested in the mobile monitoring challenge and deployed in numerous academic studies.[18,19,22−24]

(3) Continuous monitoring methods: Sensors are permanently installed in proximity to oil and gas sites and trigger follow-up surveys when they detect an anomalous emission.[19,20,25,26] Like site-level screening programs, continuous monitors allow rapid detection of large emissions while reducing the number of components that must be inspected directly.

Regulators and operators require a method for comparing the emissions reduction effectiveness of LDAR programs using continuous monitoring and site- or equipment-level screening methods to that of conventional LDAR programs. For example, Colorado's methane regulations require periodic leak detection surveys using a handheld OGI camera or an equivalent technique.[16] However, the method for determining whether a technique is equivalent is not specified. This is referred to as "technology equivalence."

A recent framework on technology equivalence developed jointly by US and Canadian scientists, industry experts, and regulators emphasizes the role of models in comparing the performance of different technologies and methods.[27] These models help evaluate new LDAR programs without the need for expensive, time-consuming, and concurrent field trials with new technologies. The Alberta Energy Regulator and the US EPA now accept modeling results as a component of applications for novel LDAR programs.[28,29] We demonstrate the Fugitive Emissions Abatement Simulation Toolkit (FEAST) as an effective model for equivalency analysis in this work.[32] Similar models have been used to approve alternative fugitive emission management programs in Alberta.[30,31]

Previous work has compared the performance of OGI-based detection methods to alternative detection methods and shown that their performance depends on the properties of the oil and gas basin where they are applied.[30,32] In this work, we critically explore the trade-offs across several technology and LDAR program parameters that help achive equivalent emissions reduction compared to existing methane mitigation policies. The modeling approach presented here accommodates any component-level or site-level survey-based LDAR program and provides recommendations for the design of cost-effective emission mitigation policies. To demonstrate the equivalency framework, we simulate both component and site-level survey methods with a broad range of sensitivities in this work. An

OGI model is included in component level-survey simulations to model existing policy scenarios.

Our approach illustrates how FEAST can provide the modeling support required by the equivalency framework.[27] While this work focuses on upstream facilities, it can be adapted to other sectors of the oil and gas supply chain. All model code and associated documentation is made publicly available as part of this publication for use by scientists, operators, and regulatory agencies.

## 2. METHODS

FEAST combines a stochastic model of methane emissions at upstream oil and gas facilities with a model of leak detection and repair (LDAR) programs to estimate the efficacy and cost of methane mitigation.[32] All simulation settings used in this work are further documented in the Supporting Information (SI, Sections S2 and S3). A detailed description of the underlying model construction can be found in ref 32.

**2.1. Facility Descriptions—Activity Factors.** Effective representation of methane emissions from upstream facilities requires both activity factors and emission characteristics corresponding to specific oil and gas basins. In this work, we use publicly available data from the U.S. EPA Greenhouse Gas Reporting Program (GHGRP) and the Colorado Oil and Gas Conservation Commission (COGCC) to create an activity model representative of sites in the Denver-Julesburg (DJ) basin.[34] On average, there are 1.9 wells per site in the DJ-basin, with a range between 1 and 51 wells per site. Activity data for this work also include component counts and frequency of unloading events (SI, Section S2).

**2.2. Emission Descriptions—Emission Factors.** FEAST simulates vents and fugitive emissions. Vents are emissions that occur by design, such as emissions from gas-driven pneumatic devices, and pressure-release valves. We also model liquid unloading events. For this work, unloading events are represented based on the total number of events and emissions reported to the GHGRP,[33] while all other vents are approximated by drawing emission rates from an empirical distribution of observed emissions.

The fugitive emission model is characterized by an empirical emission distribution and a leak production rate [# new emissions/site-year]. FEAST simulates new leaks as independent random events in a Poisson process. The leak production rate is estimated based on the number of emissions found in repeated surveys of production equipment including tanks, pneumatics, and fugitive equipment under Colorado's OGI survey regulations.[16,35] The empirical emission data set is compiled from component-level emission measurements from five recent publicly available studies.[17,36−39] The studies included here did not distinguish between vents and leaks. In this work, we assume that 46% of emissions simulated from the data set are vents (see the SI, Section S4.4 for additional detail). The emission rate for each emission is drawn with replacement from the data set. This approach is preferred compared to standard EPA emission factor approach because of the importance of superemitters and skewed emissions distributions on the mitigation outcomes of LDAR programs. Additional information describing the data is available in the SI, Section S2.

Several prior studies have demonstrated the highly skewed nature of methane emissions, with the top 5% of sites contributing to between 20 and 70% of total emissions depending on the geologic basin surveyed.[40−43] In a sensitivity

analysis, we use a parametric emission-size distribution to vary the contribution of the largest emitters to total emissions to understand how variability between basins will affect mitigation outcomes. The parametric distribution was defined such that emissions from the 80th percentile and larger were drawn from a power-law distribution rather than the empirical distribution. The exponent characterizing the power law was then adjusted to achieve a range of skews in the emission distribution as observed in field campaigns throughout North America. The parameterization maintains the median emission rate while exploring the range of equivalency conditions under different emission distributions (see SI, Section S2.3.3).

**2.3. Model Simulation.** Every FEAST run simulates undirected inspection and maintenance (UDIM) activities in addition to LDAR programs. The UDIM model represents voluntary maintenance activities undertaken by operators. The UDIM model causes the total number of emissions to equilibrate over time in the absence of an LDAR program as UDIM repairs offset the occurrence of new fugitive emissions. In practice, emissions may increase or decrease over time as faults in new equipment are addressed (decreasing emissions), old equipment becomes more leak prone (increasing emissions) or other phenomena affect trends in emissions.[30] UDIM repair rates that result in increasing or decreasing emissions over time are explored in the SI, Section S4. LDAR models simulate regulatory LDAR surveys that occur in addition to UDIM activities. Comparing emissions in a UDIM-only scenario to an LDAR program helps calibrate the model by comparing model-derived emission reduction from OGI-based LDAR surveys to recent field data and regulatory models.[16,17]

**2.4. LDAR Programs.** In this study, we simulate two types of LDAR programs: component-level detection programs and tiered detection programs. Component-level detection programs evaluate every component for emissions independently and identify the source of emissions at the time of detection. Tiered detection methods take a hybrid approach to leak detection: an initial survey to perform site-level screening that flags sites for follow-up with a component-level survey to identify components for repair. Both site-level and component-level detection is determined stochastically using probability of detection (PoD) curves dependent on emission rate and the method's operational envelope (SI, Section S3).[35]

*2.4.1. Component-Level Survey.* OGI camera surveys are an example of a component-level survey. Different component-level survey methods are distinguished by their probability of detection (PoD) curves, survey speed, and cost, as shown in Table 1. The median detection limit is defined as the emission rate at which the probability of detection is 50% (SI, Section S3). Several recent empirical, peer-reviewed performance assessment studies are used to parameterize and validate the PoD curves.[18,35,44] The costs represent the full cost of leak detection that would be charged by a service provider, similar

to the approach recently used by the EPA.[45] The per-site cost reported in Table 1 for OGI surveys is calculated using three parameters: the component-level survey speed (741 components/h), an hourly billing rate ($360/h), and the number of components per site. The per-site cost for an aerial screening survey is input to FEAST directly based on publicly available estimates. Leaks detected by a component-level survey are immediately passed to the repair process that eliminates the leak one day later.

*2.4.2. Tiered Surveys.* Tiered detection programs use a screening method to identify production sites with high emission rates, similar to several existing aerial technologies.[19] Like the component-level detection model, the probability of detection curve is modeled as a sigmoid based on empirical observations in recent peer-reviewed studies (Table 1 and SI, Section S3).[18] For these simulations, all sites with emissions that are detected by the screening method are flagged for follow up by an OGI camera inspection to identify the source(s) of the emissions.

**2.5. Simulation Settings.** Simulations represent emissions from 100 well sites over 3 years with a time resolution of 1 h. 300 Monte Carlo iterations were completed for every LDAR program and emission scenario.

**2.6. Mitigation and Equivalency Calculations.** Mitigation is calculated based on the difference in emissions between the UDIM and LDAR scenarios. This definition of mitigation is useful for comparing our results to regulatory projections (e.g. ref 45), but carries uncertainty in the UDIM repair rate into the results.[30] The framework presented here can be employed by regulators, operators, or service providers to determine which LDAR programs can achieve equivalent emission reductions.

SI, Section S4 introduces an equivalency metric that compares component-level and tiered methods to each other without reference to the UDIM scenario. Since variability in the UDIM repair rate tends to affect both classes of LDAR program similarly, the impact of UDIM uncertainty on results is partly canceled out.[30]

## 3. RESULTS

We present a series of results that evaluate equivalency and cost effectiveness between LDAR programs with increasing degrees of freedom such as technology choice, survey frequency, and detection threshold. The results demonstrate the equivalency framework applied to the Denver-Julesberg basin for tiered and component-level surveys. Since the model and data are public, it can be adapted to other basins with different emission distribution characteristics.

**3.1. Emission Mitigation under OGI and Tiered LDAR Programs.** Observing the output from a single Monte Carlo iteration of FEAST for one tiered program and one component-level program highlights some of the critical features of the model. Figure 1A shows the first 30 days of emissions from a single FEAST iteration of three scenarios: UDIM, semi-annual OGI-based component-level program, and semi-annual Aerial + OGI tiered program. Since LDAR programs only affect leaks, vented emissions are identical across all scenarios. Liquid unloading events result in short-duration spikes that drive the emission rate to over 20 kg/day per well. The rapid survey speed of the tiered detection method allows emissions to be found more quickly than a traditional OGI survey in the first few days of the simulation, but the OGI method surpasses the Aerial + OGI program by

**Table 1. Key Parameters of the OGI-Based Component-Level Detection Method and Tiered Aerial Detection Method Used in This Study**

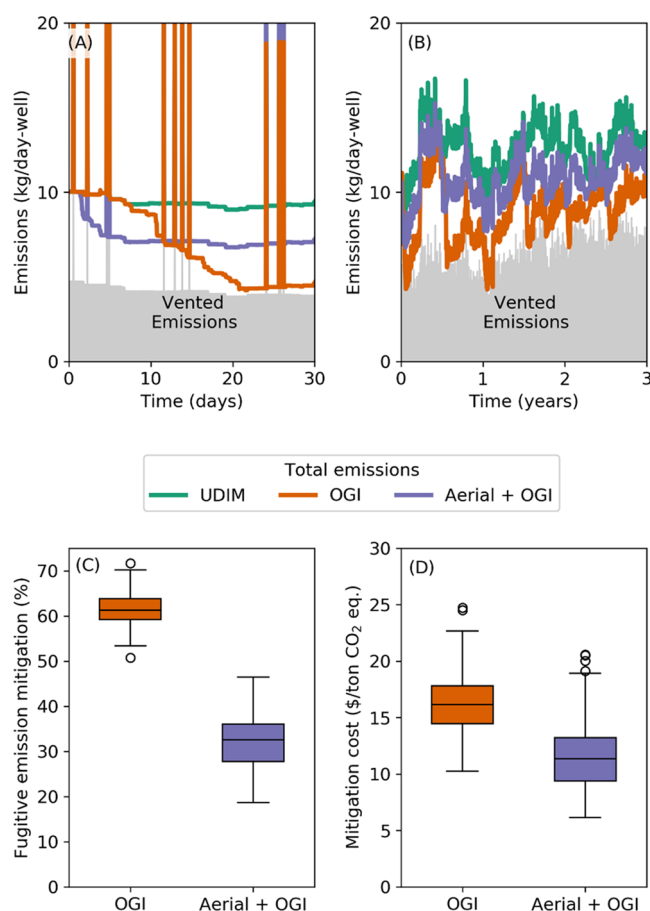| Method | Median Detection Limit (kg/day) | Survey Speed | Cost ($/site) |
|---|---|---|---|
| OGI (component level) | 2 | 6 sites/day | $600/site |
| Aerial (tiered) | 94 | 222 sites/day | $100/site |

**Figure 1.** Results of FEAST simulations representing semi-annual OGI surveys ("OGI") and aerial screening with OGI follow up ("Aerial + OGI") at high-emitting sites. (A) Thirty days of hourly emissions in a single realization generated by FEAST. (B) One-day moving average emission rate from a single realization under three LDAR scenarios over the entire simulation period of 3 years. (C) Distribution of mitigation achieved by OGI and Aerial + OGI LDAR programs. (D) Distribution of mitigation costs for the OGI and Aerial + OGI LDAR programs. Outliers are greater than the 75th percentile by more than 1.5 times the interquartile range.

the end of the 30 day period because the OGI survey is more sensitive (lower detection threshold) than the aerial survey.

Extending Figure 1A over the full 3-year duration of the simulation with semi-annual survey frequency reveals long-term trends in emissions under each LDAR scenario. The time series in Figure 1B is smoothed to daily average emission rates. Less sensitive than the OGI camera, the aerial survey identifies fewer sites with emissions compared to OGI. Thus, fewer sites are flagged for follow-up repair, resulting in higher average emissions when the two methods have the same survey frequency.

Reviewing results from many iterations illustrates the range of results that are likely in a particular scenario. Figure 1C shows the emission mitigation achieved under both LDAR programs, relative to emissions in the UDIM scenario. A semiannual OGI-based LDAR survey results in fugitive emission mitigation of approximately 60%, similar to EPA's assumptions in its methane regulations.[45] By comparison, the Aerial + OGI LDAR program achieves emission mitigation of about 33%, less than the conventional OGI survey. In this scenario, the two LDAR programs are not equivalent. The

error bars represent variability from 300 Monte Carlo iterations of LDAR programs. Although FEAST models detection as a probabilistic process, the uncertainty range shown in Figure 1C is driven by variability in the emission simulation rather than the detection simulation (see SI, Figure S9). Therefore, the relative performance of the two simulated LDAR programs to each other is more certain than the absolute emission reductions in either case.

Mitigation cost results are also stochastic. Although the Aerial + OGI program achieves less mitigation than the conventional OGI program, Figure 1D shows that it has a lower cost per ton of avoided $CO_2$ equivalent emissions. The mitigation cost for the Aerial + OGI program is $11/tCO2e, about 31% lower than the $16/tCO2e cost for OGI-based mitigation. In this example, the Aerial survey flagged just 10% of sites for follow-up surveys.

**3.2. Mitigation Equivalence Dependence on Survey Frequency.** Since an aerial survey will not detect as many emissions as an OGI survey, the Aerial + OGI program must survey more frequently to achieve equivalent emission reductions. Figure 2 shows the impact of survey frequency on the mitigation and cost of the two LDAR programs.

Figure 2A compares the component-level and site-level emission rate distributions under UDIM conditions to the median detection thresholds of the OGI and Aerial technology (see the SI, Figure S2 for additional details of the PoD curve). Overall, 94% of emissions come from sources larger than the median detection threshold of the OGI camera. However, only 41% of emissions come from sites with a total emission rate greater than the median detection threshold of the Aerial technology.

Figure 2B shows the emission mitigation achieved through both LDAR programs as a function of survey frequency. For the conventional OGI-based survey, increasing survey frequency from 2 to 4 times per year increases mitigation from 60 to 73%. This is similar to the emission mitigation expected in federal regulations, where semiannual and quarterly surveys reduce emissions by 60 and 80%, respectively.[45] Thus, model parameters here reproduce emission mitigation current regulations expect to be achieved under different OGI-based LDAR survey frequencies.

Increasing survey frequency reduces the duration of fugitive emissions. In the UDIM scenario, leaks have an average duration of 208 days. Under an LDAR program, leaks that are large enough to be detected will have an average duration of approximately one-half the time between surveys: for example, quarterly surveys result in an average duration of approximately 45 days for large leaks. LDAR programs mitigate emissions by reducing their duration.

Consider a mitigation target of a 40% reduction in fugitive emissions. The conventional OGI-based LDAR survey can achieve this mitigation target with an annual survey. Equivalently, the tiered Aerial + OGI LDAR program achieves 40% mitigation if the survey frequency is increased to approximately three surveys per year. Higher levels of mitigation can be achieved with either program if the survey frequency is increased further, although the aerial survey cannot achieve 80% mitigation even with monthly surveys. While increasing the survey frequency decreases the duration of detected emissions, emissions much smaller than the detection threshold remain unaffected even at high survey frequencies. The detection threshold of a screening technology
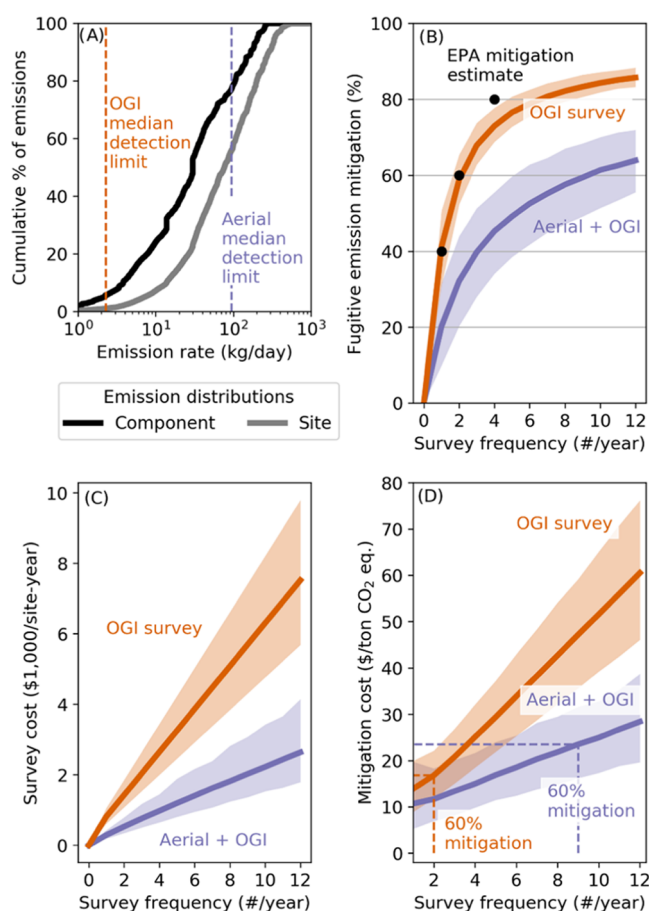
**Figure 2.** LDAR simulation results for an OGI detection threshold of 2 kg/day and an aerial detection threshold of 94 kg/day. (A) Component-level and site-level cumulative emission distributions with dashed lines indicating the median detection limit for the simulated Aerial and OGI detection methods. (B–D) Fugitive emission mitigation, survey cost, and mitigation cost with OGI and Aerial + OGI LDAR programs over a range of survey frequencies. Uncertainty ranges represent the 95% confidence interval generated by Monte Carlo iterations.

thus places an effective upper bound on the amount of mitigation that can be achieved.

Figure 2C shows that the cost of surveys for each LDAR program is proportional to the survey frequency. Prior studies have shown that the majority of costs associated with the implementation of LDAR programs are reflected in the survey costs.[46−48] The US EPA's own analysis of its methane regulations shows that semiannual OGI-based LDAR surveys contribute over 70% of the total cost of the LDAR program. The simulations shown in Figure 2B,C suggest 60% fugitive emission reduction using either semiannual OGI surveys or nine aerial surveys per year with OGI follow up. Under our cost assumptions, semiannual OGI surveys incur costs of $1400/site-year compared to $2000/site-year to achieve equivalent mitigation with more frequent Aerial + OGI surveys.

The results of Figure 2B,C were combined to generate Figure 2D: the cost per metric ton of $CO_2$ equivalent emissions mitigated. The nonlinear mitigation curve of Figure 2B causes the mitigation cost to increase more slowly for survey frequencies less than 3/year: as survey frequency increases from zero, mitigation also increases partially offsetting the added survey costs. At higher survey frequencies, mitigation approaches its asymptote resulting in near-linear growth in mitigation cost. The result illustrates that the marginal cost of mitigation increases as the survey frequency increases.

**3.3. Cost Effectiveness of Equivalent LDAR Programs Requires Optimization Across Survey Frequency and Detection Threshold.** The cost effectiveness of emission mitigation depends on both the leak detection method and the survey frequency. Here, we explore the cost effectiveness of fugitive emissions mitigation ($/tCO2e) by modeling two generic leak detection methods—component-level surveys at an average cost of $600/site and site-level surveys at $100/site. The results highlight the impact of sensitivity and survey frequency, while the cost per-site inspection remains constant. In practice, we find that survey costs are dictated more by the speed of the platform (aerial vs ground-based surveys) rather than the sensitivity of the methane sensor, thus justifying the constant per-site inspection costs. For example, Schwietzke et al. report that the less sensitive technology (a detection limit approximately 9 times less sensitive than the alternative) incurred a 50% greater cost in their study.[22]
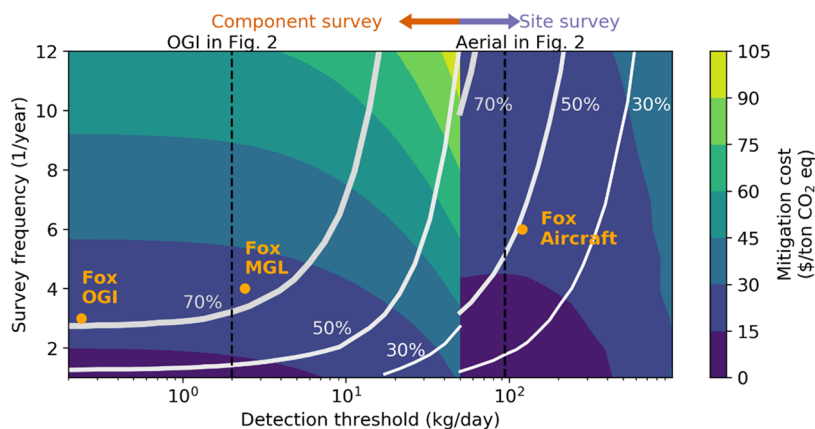


**Figure 3.** $CO_2$ equivalent mitigation cost of modeled technologies over a range of survey frequencies and detection thresholds. White contour lines indicate fugitive emission mitigation percentages with the line thickness proportional to mitigation level, while the color map indicates mitigation cost. Results from LDAR-Sim for an OGI survey, Mobile Gas Laboratory (MGL), and aircraft surveys are shown in orange dots.[30]

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Figure 3 illustrates mitigation cost as a function of detection threshold and survey frequency of LDAR programs. Horizontal transects across the mitigation contours reveal the impact of increasing the detection threshold while holding survey frequency constant. For small detection thresholds between 1 and 10 kg/day (high sensitivity), there is little change in mitigation as sensitivity increases because small emitters account for a small fraction of total emissions. However, as the detection threshold exceeds 10 kg/day, mitigation is more sensitive to the detection threshold. Thus, while increasing the sensitivity of detection technology can improve mitigation outcomes, the marginal improvement in sensitivity below about 10 kg/day does not result in a corresponding increase in emission mitigation. One can therefore trade high sensitivity for lower cost without adverse mitigation outcomes.

Considering the color map of Figure 3 reveals trends in mitigation *cost*. Continuing with the example site-level detection threshold of 94 kg/day, the mitigation cost is 11 $/tCO2e for a survey frequency of 2/year but increases to 22 $/tCO2e for a survey frequency of 8/year. In addition, mitigation cost increases as the detection threshold increases. This trend occurs because the cost per component or site surveyed is independent of sensitivity. The survey cost of the component-level programs remains constant while the total mitigation decreases, resulting in an overall increase in mitigation cost. By contrast, the costs of tiered programs decline as the detection threshold increases because fewer sites are flagged for follow-up surveys. However, the results show that the decrease in cost due to follow-up surveys is not sufficient to offset the decline in mitigation caused by increasing the detection threshold.

Tiered detection programs must efficiently direct ground crews to achieve sufficient emission mitigation without incurring secondary survey costs that exceed the savings achieved by the site-level survey. Tiered methods that identify high-emitting equipment rather than sites may be more successful if they can significantly reduce the time on site required of ground crews and avoid misallocating ground crews due to vented emissions. Our results also show that tiered detection programs are more cost effective if the mitigation goal is less stringent. For example, Figure 3 shows tiered methods with a site-level detection threshold of 60 kg/day can achieve 50% mitigation with quarterly surveys at a cost of $15/tCO2e, lower than the equivalent semiannual OGI-based LDAR survey cost of $17/tCO2e. The results from Figure 3 are sensitive to the underlying emission rate distribution as described in the following section. Figure 3 is consistent with results from Fox et al.[30] and expands on those results. The LDAR programs used to demonstrate LDAR-Sim are indicated in orange. While Fox et al. evaluate three different OGI programs differentiated by their operating envelope at different wind speeds and precipitation rates, they collapse into one program along the two dimensions shown in Figure 3. We do not evaluate the impact of meteorological conditions in this work, so the reference condition in Fox et al. is the closest comparison due to its wide operating envelope. In that scenario, Fox reports a fugitive emission rate of approximately 2.5−5 kg/day-site, compared to 2.7−5.3 (95% confidence interval) in this work. The results are consistent despite OGI being treated as an order of magnitude less sensitive in this work than in Fox et al. Our assumption in this work is based on empirical results from field trials designed to simulate realistic conditions, while Fox et al. reference the 3 m sensitivity

measured by Ravikumar et al.[35] As the contours show in Figure 3, there is little change in mitigation as the detector sensitivity improves beyond 2 kg/day.

Equivalence results are also consistent with Fox et al. Using the parameters for component-level and aerial site-level surveys from Fox et al. in our model, we find that they do not achieve equivalent emissions reductions, consistent with the study's findings. Although not directly comparable, we can approximate the Mobile Ground Laboratory (MGL) model by Fox et al. using our component-level results with similar detection sensitivity. As Fox concluded, our results suggest that the MGL program will achieve similar mitigation to the reference program. Our results build on the results from Fox et al. by exploring the full sensitivity-survey frequency design space. Any survey-based LDAR program can be placed in this space, and the mitigation potential evaluated.

### 3.4. "Equivalence" Depends on the Natural Gas Basin Where a Technology Is Applied.
The skew of an emission distribution affects equivalence between LDAR programs. An LDAR program that specializes in quickly identifying large leaks will perform better if emission distributions are more skewed because high-emitting sites will account for a greater fraction of total emissions. Conversely, a component-level method that surveys less frequently but has a more sensitive detector will achieve a better mitigation fraction in less skewed distributions because it will not allow midsize leaks to persist indefinitely. While Figures 1−3 rely on the empirical emission distribution compiled for this work, this section explores how equivalence is sensitive to changes in the emission distribution.

Figure 4 shows the technology detection threshold required to achieve a target emission mitigation level across different
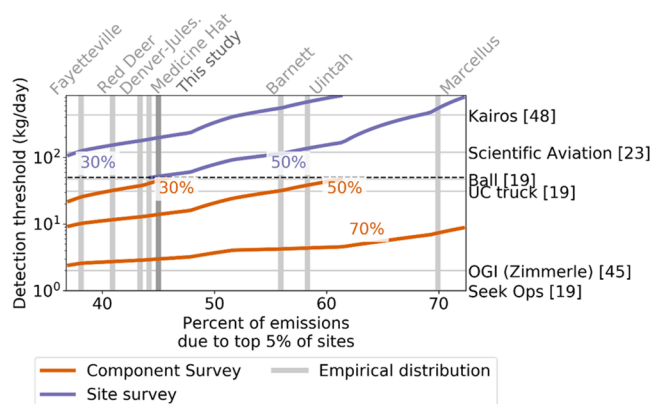


**Figure 4.** Effect of emission-size distribution on the detection threshold required to achieve a given mitigation target. Purple and orange curves indicate the detection threshold required to achieve mitigation for component- and site-level surveys, respectively. Follow-up survey sensitivity is kept constant for all site survey methods. Gray bars indicate the emission distribution skew observed in eight empirical studies of site-level emissions.

emission distributions. The orange and purple curves represent mitigation under the component level and tiered detection programs, respectively. In all cases, the survey frequency was set to 6 surveys per year, while the detection threshold was varied to achieve the target emission mitigation rate.

In a highly skewed emission distribution as observed in the Uintah or Marcellus basin, 50% mitigation can be achieved with a tiered detection program that has a detection threshold of 200 kg/day. However, a detection threshold of 50 kg/day

would be required to achieve the same level of mitigation in a less skewed distribution as observed in Medicine Hat in Alberta. More skewed distributions allow the same mitigation targets to be achieved with a higher detection threshold, resulting in a positive slope for all tiered and component surveys modeled in Figure 4.

The vertical gray lines show results from empirical studies conducted in the last 5 years from U.S. and Canadian shale basins. The range of skew measured in various basins shown in Figure 4 gives an indication of the combined uncertainty and variability that exists in emission distributions. Furthermore, the distribution of emissions that occur in a particular basin may evolve over time due to maturing infrastructure, new wells, and production decline. An alternative LDAR program may become more or less effective in comparison to OGI over time.

## 4. DISCUSSION AND STUDY LIMITATIONS

According to the EPA greenhouse gas inventory, more than 5 million tons of methane leaked from US natural gas infrastructure in 2018.[1] New mobile and fixed-sensor technologies could provide a cost-effective approach to reduce emissions. Yet, regulatory approval of these new methods critically depends on a demonstration of equivalence to existing LDAR approaches. The equivalence analysis described here fulfills the modeling requirements of the equivalency framework developed by Fox et al. and highlights the sensitivity of results to the underlying emission model.[27]

Our results build on earlier work by Fox et al., Schwietzke et al., the EPA, and others to develop equivalency estimates and cost models.[22,30,45] The original FEAST model relied on a physics-based representation of detection technologies and did not support LDAR programs that combined multiple technologies.[32] Empirical probability of detection curves was introduced to FEAST in 2018.[49] Fox et al. introduced an agent-based model that supports arbitrary combinations of detection technologies and used it to analyze several example LDAR programs, including three distinct OGI programs and two-tiered programs.[30] Each program is compared to the reference OGI program to demonstrate equivalence. Here, we introduce support for tiered programs in FEAST and map the complete sensitivity-survey frequency design space. More critically, we make the FEAST model publicly available to help operators, regulators, and technology developers evaluate LDAR programs across basins and new leak detection paradigms.

The cost modeling that we used makes a distinction between component-level and site-level surveys. The costs of component-level surveys were calculated based on the number of components at a site. We calibrated the cost-per-component so that the average site had a cost of $600—consistent with the EPA cost estimate of $600/site for OGI surveys. Our model expands on the EPA's work by introducing a realistic distribution of site sizes that affect survey costs. This feature is important for tiered detection programs because there may be a correlation between site size and the probability that a follow-up survey is required: the average number of components per site flagged for follow up may be larger than the average number of components per site.

Equivalent emission mitigation can be achieved with a broad range of sensitivities by choosing the appropriate survey frequency and/or using a tiered detection approach. Tiered detection approaches take advantage of the heavy-tailed nature

of emission distributions to allocate resources to the largest emissions, while component-level surveys invest the same amount of time in identifying emitters of all sizes. Tiered approaches must be efficient in dispatching ground crews to offset the additional costs from increased survey frequencies.

Depending on their approach, LDAR programs will be affected differently by the emission-size distribution. While the composite emission distribution used in this work falls within the range of emission distributions that are observed in the United States, Figure 4 shows that no distribution can accurately represent all basins. Furthermore, the uncertainty in the tail of the component-level emission distribution remains an important source of uncertainty in mitigation modeling. Accurately representing mitigation requires improved measurements of emission distributions.

Our analysis described mitigation in terms of the reduction in average emission per site. This approach is a natural choice in the context of regulations that provide mitigation targets as a percentage of current emissions, but program efficacy could also be measured by emissions intensity—that is, the mass of methane emitted per unit of gas produced. An emission intensity standard would reduce the sensitivity of results to emission distribution skew: highly skewed distributions allow less sensitive detectors to achieve large percentage reductions in emissions, but the smaller emissions that might need to be targeted to achieve an emission intensity standard will persist.

Uncertainty in the leak production rate and other input variables results in broad confidence intervals surrounding equivalency analysis. Running many Monte Carlo iterations of FEAST allows users to accurately assess the expectation value and range of emissions that are likely with different LDAR programs, but it does not assess the impact of parameter uncertainty. The sensitivity analysis presented in the SI, Section S4 explores the impact of changing input parameters over a realistic range. With existing data, the expectation value for the most likely emission rate under a novel LDAR program must be much less than the most likely emission rate under an OGI program for a regulator to be 95% confident that the true effect of the novel program is at least as good as a conventional OGI program. Improving the precision of the equivalency analysis will reduce the performance burden on novel technologies. Reducing uncertainty in the leak production rate estimate will improve precision the most, followed by developing basin-specific emission distributions.

The sensitivity results confirm prior findings that demonstrate the importance of improving leak production rate estimates. In this work, we use data from CDPHE to estimate the leak production rate and rely on measured emissions at sites without frequent LDAR surveys to estimate a steady-state emission rate. This analysis adds a new estimate of the leak production rate to the literature, but the accuracy is still limited by repairs that may occur between LDAR surveys, the assumption of steady-state emissions, and the use of data from multiple basins. We discuss a method for improving this precision with further empirical work in the SI, Section S4.2.

Our treatment of vented emissions is similar to our treatment of fugitive emissions: we draw emission rates from the same empirical distribution in both cases, and then add unloading events with a predetermined emission rate. This approach allows us to capture the impact of having many emissions that cannot be repaired but does not capture the dynamic nature of many vents nor the likelihood that vented emissions and fugitive emissions follow different size

distributions. These two factors—vent dynamics and vent size distributions—will be critical to future work assessing the value of using emission quantification estimates and vent estimates to make dispatch decisions. Coupling FEAST with a process-based model similar to that described by Cardoso-Saldon et al.[50] will provide the vent resolution required for that type of analysis.

We draw the following conclusions from the results of this work that can aid operators and regulatory agencies in developing LDAR programs using new methane detection technologies:

(1) Equivalent emission mitigation can be achieved by LDAR programs with different detection thresholds by varying the survey frequency.

(2) Median detection threshold of new technologies, to first order, presents effective lower and upper bounds for emission mitigation. At the lower end, decreasing the detection threshold below 10 kg/day does not increase mitigation outcomes proportionally because of skewed leak-size distributions. At the upper end, emission mitigation with high median detection threshold technologies does not increase in proportion to survey frequency as emissions smaller than the detection threshold remain unaffected even at high survey frequencies.

(3) Vented emissions play a critical role in the cost effectiveness of tiered detection programs that direct ground crews based on site-level emission detection. Without a reliable way to differentiate sites with high vented emissions from those with high fugitive emissions, tiered programs risk directing ground crews to many sites with little mitigation benefit, thereby increasing costs.

(4) The survey frequency and detection threshold required for equivalent emission mitigation will depend on the emission-size distribution in the basin where the LDAR program is applied. Evaluation of the efficacy of LDAR programs and technology equivalence periodically to account for (a) changes to emission-size distribution, and (b) reduction in emissions over time will be critical to ensure mitigation targets are achieved throughout the duration of the program.

New methane detection technologies and platforms represent an opportunity to cost effectively address methane emissions from the oil and gas industry. While this work focused on survey-based methods, the equivalency framework can be applied to continuous monitors equally well once they are supported in future releases of FEAST. The degrees of freedom in LDAR program parameters such as technology choice, hybrid detection, survey frequency, and detection threshold provide a method to design methane mitigation policies that best tackle issues specific to the gas field or operator. As states and countries around the world converge on methane emissions as a cost-effective, near-term approach to address climate change, FEAST is a quantitative tool for assessing new technologies, evaluating the outcomes of mitigation programs, and achieving methane mitigation targets. Future work on this model will enable evaluation of satellite technologies and continuous monitoring systems to provide a near real-time monitoring of methane emissions across the world.

The framework can be applied to transmission and distribution sectors of the natural gas industry in addition to the production sector if emission rate distributions, leak production rates, and repair costs are adjusted accordingly. In addition, the transmission and distribution sectors may require modeling support for leaks that grow or change over time. Repair costs are small in the simulations because in most cases, LDAR programs simply cause repairs to occur more quickly than they otherwise would. If UDIM repair rates are lower or nonexistent in other sectors, then repair costs may be more significant.

In light of the potential use of this model in regulatory rule making, all model code and documentation are made publicly available as part of this publication, including any future updates.

## ■ ASSOCIATED CONTENT

**Ⓢ Supporting Information**

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.1c03071.

> Additional details on the emissions model including activity data and emissions distribution, LDAR program parameters, and technology descriptions; tabular data and figures on sensitivity analysis for leak-size distributions, leak production rate, UDIM repair rate, vent fraction, equivalence ratios, and other input parameters, difference between emissions variability and detection variability (PDF)

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**Notes**

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## ■ ACKNOWLEDGMENTS

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